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Mine ventilator fault diagnosis based on information fusion technique

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Abstract

A fault diagnosis method of multi-fault-featured information fusion is proposed to improve accuracy of fault diagnosis. The multi information of this method includes stator current signal, axial vibration signal, and radial vibration signal. These collected signals are processed by wavelet analysis to extract the fault feather. Based on each type of information, primary conclusion is achieved by neural networks. In order to achieve the finally conclusion, Dempster combination rule is used to realize information fusion. The experiment result shows that the reliability of fault diagnosis with the multi-fault characteristic information fusion is improved evidently and its uncertainty decreases remarkably. It proves that the proposed method can improve the accuracy and reliability of fault diagnosis.

Keywords: evidential theory; information fusion; fault diagnosis; mine ventilator

1. Introduction

The main ventilator is very important for the safety of coal mine production. Fault diagnosis is a reliable method to maintain the fan to operate safely, reliably, and economically. At present, there are several fault diagnosis methods for the fan. One of which is to monitor the temperature of fan bearing, another one is spectrum analysis for vibration signal. These traditional methods have certain limitation in that the fault feature extraction and recognition is realized artificially. The level of diagnosis depends on the knowledge and experience of technicians. To solve this problem, several intelligent fault diagnosis technique has been proposed by researchers such as neural network, wavelet analysis, support vector machine, and so on[1,2].

The common problem of the above methods is that their diagnosis conclusion is achieved based on one type of signal only such as vibration signal or stator current signal. But the fault reason of main fan is complicated and various. It is uncertain and unreliable when using only one signal. Using information fusion technique to integrated

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use multi-fault characteristic information can improve accuracy and decrease uncertainty of fault diagnosis

D-S evidence theory, also known as the theory of evidence, was first proposed by Dempster in 1967[3]. Shafer carried out a further research [4]. D-S evidence theory has a strong ability to deal with uncertain information. So it has a wide range of applications in the field of multi-target recognition and multi-sensor data fusion[5,6].

A fault diagnosis method using multi-sensor data of main fan is presented in this paper. Stator current signal, axial vibration signal and radial vibration signal are collected. Wavelet analysis is used to extract fault feature from these signals. Neural network is used to obtain the primary conclusion based on the fault feather of each information. The Dempster combination rule is used to realize information fusion to achieve finally conclusion.

2. Basic concept of evidence theory

In this section, we introduce the basic concept of evidence theory briefly. More details can be found in [3, 4].

Let U be a finite nonempty set called the frame of discernment (the frame for short). The mapping $\text{bel}: 2^U \rightarrow [0,1]$ is an (unnormalized) belief function if and only if there exists a basic belief assignment $m: 2^U \rightarrow [0,1]$ such that:

$$\begin{cases} m(\phi) = 0 \\ \sum_{A \subseteq U} m(A) = 1 \end{cases} \quad (1)$$

Those subsets A such that $m(A) > 0$ are called the focal elements. Intuitively, the value $m(A)$ represents the part of belief supporting the fact that A occurs and cannot support any more specific event (due to the lack of information).

Two bodies of evidence m_1 and m_2 can be combined with Dempster's orthogonal rule as follows:

$$m(C) = \begin{cases} \frac{\sum_{A_i \cap B_j = C} m_1(A_i) m_2(B_j)}{1 - K} & \forall A \subset U, C \neq \phi \\ 0 & C = \phi \end{cases} \quad (2)$$

Where

$$K = \sum_{A_i \cap B_j = \phi} m_1(A_i) m_2(B_j) \quad (3)$$

Equations (2) and (3) are the core of D-S evidence theory and they can combine several individual evidences together. K is often interpreted as a measure of conflict between different sources.

3. The mine ventilator fault diagnosis based on information fusion technique

3.1. Fault feature extraction

In the field of artificially intelligent faults diagnosis of mine fan, it is important to extract the features of any typical fault.

When the main fan goes wrong, the energy of each subset frequency bands changes. The energy of each subset frequency bands includes all the information of diagnosis. When the main fan works under different conditions, energy of some subset frequency bands should be reinforced or weakened. So the energy of each subset frequency bands is regarded as the feature factor which is obtained by wavelet packet transform (WPT) from the original signal.

Energy feature factor can be constructed through the following process:

(1) Decomposing the original signal on level j , then we get 2^j subsets. 3 level tree structure of wavelet packet analysis is shown in Fig. 1.

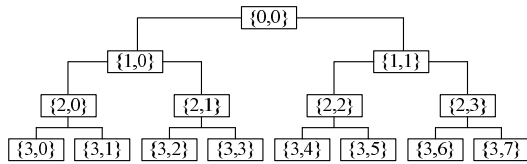


Fig. 1. Three-layer tree structure of wavelet packet analysis

(2) Computing energy $E(j,k)$ of each subset and total energy of the original signal E :

$$E = \sum_{k=0}^{2^j-1} E(j,k), \quad E(j,k) = \sum_{i=1}^{N/2^j} (x_{j,k}[i])^2 \quad (4)$$

In Equation(4), N is the data length of the analyzed signal; $x_{j,k}[i]$ the WPT coefficients of the k subset sequence in level j ; and k the number of subset from $0 \sim 2^j-1$, it can be denoted by binary code taking no account of its sign, whose length is j .

(3) Constructing energy feature factor T .

The energy normalized feature factor $e(j, k)$ of the k subset sequence on level j can be constructed as:

$$e(j,k) = E(j,k) / E = E(j,k) / \sum_{k=0}^{2^j-1} E(j,k) \quad (5)$$

The feature factor T of 3 level tree structure is defined as:

$$T = [e_{30}, e_{31}, e_{32}, e_{33}, e_{34}, e_{35}, e_{36}, e_{37}] \quad (6)$$

The feature factor T is extracted as fault Eigenvalue which will be the input of neural network in order to obtain the primary conclusion.

3.2. Local diagnosis

After fault feather has been exacted, we use neural network to realize feather recognition. We use several neural networks, with each network recognizing feather of one type signal. The input of neural network is T , the output is a primary diagnosis conclusion. D-S evidential theory is used as global diagnosis to gain a unified result. This conclusion is achieved from one type of signal, so this is local diagnosis.

The radial basis function (RBF) network has been widely studied and applied in system dynamics modeling, pattern recognition and prediction. A fundamental problem in RBF network modeling is to achieve a network with a parsimonious model structure producing good generalization. RAN(Resource Allocating Network) can allocate RBF dynamic networks and build more parsimonious model structure than traditional RBF network.

The RAN is a two-layer network (fig. 2). This network consists of n input as well as m output.

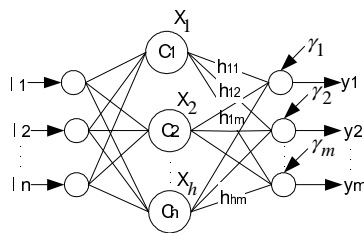


Fig. 2. Structure of RAN

The first layer consists of units that respond to only a local region of the space of input values. The second layer aggregates outputs from these units and creates the function that approximates the input-output mapping over the entire space. More detail of RAN should be found in Ref.[7].

RAN is used to realize fault feature recognition. The output is a fault code. In view that the usually fault type of main fan is the rotor imbalance, shaft-misalignment, and vane fault imbalance, the output code is defined as: (0 0 1), (0 1 0), (1 0 0). This output is a primary conclusion and should be fused with other primary conclusion of other network.

4. Case study

In our experiment, the stator current signal, axial vibration signal, and radial vibration signal are collected under three typical running states of rotor imbalance, shaft-misalignment and vane fault. The sample frequency is 5000Hz. The fault type is defined as {F1, F2, F3}. 60 group of Eigenvalue are achieved by wavelet packet transform, which 40 group are used to train RAN, the other 20 group are used to test. Several Eigenvalue of each fault type is shown in Tab.1. After local diagnosis, D-S evidential theory is used as global diagnosis to gain a final result. The final fault diagnosis conclusion is shown in Tab.2.

Table 1. Eigenvalue of each fault type

Fault type	E ₁ [3,0]	E ₂ [3,1]	E ₃ [3,2]	E ₄ [3,3]	E ₅ [3,4]	E ₆ [3,5]	E ₇ [3,6]	E ₈ [3,7]
F ₁	17.8149	1.2676	0.6772	0.4393	0.3995	0.2930	0.2516	0.3269
	19.4978	1.3734	0.7353	0.5026	0.4118	0.3079	0.2739	0.3644
F ₂	10.5191	0.7579	0.4305	0.2731	0.2633	0.2172	0.2196	0.2425
	10.7241	0.7532	0.4339	0.2754	0.2729	0.2237	0.2201	0.2353
F ₃	64.5831	4.1103	2.0629	0.4698	1.0861	0.3910	0.3770	0.3833
	64.7853	4.1141	2.0686	0.4624	1.0961	0.3930	0.3764	0.3856

Table 2. Basis probability assignments of single evidence and multi evidences

Evidence set	Sample 1			Sample 2			Sample 3		
	<i>m</i> (A)	<i>m</i> (B)	<i>m</i> (C)	<i>m</i> (A)	<i>m</i> (B)	<i>m</i> (C)	<i>m</i> (A)	<i>m</i> (B)	<i>m</i> (C)
Evidence 1	0.2728	0.1079	0.6193	0.7943	0.1222	0.0835	0.117	0.5482	0.3348
Evidence 2	0.1372	0.3071	0.5557	0.6435	0.2173	0.1392	0.2231	0.705	0.0719
Evidence 3	0.5274	0.1332	0.3394	0.872	0.1077	0.0203	0.0971	0.8055	0.0974
D-S	0.1401	0.0313	0.8286	0.9931	0.0064	0.0005	0.008	0.9846	0.0074
Actual condition	0	0	1	1	0	0	0	1	0

From Tab. 2, under the combination role of each evidence, the basic probability assignment of fault object increase obviously. From output of every single fault diagnosis network, every single fault diagnosis system's result is uncertainty. After fusion, this diagnosis result is agreed with actual fault, showing that the method of combining Multi-information with D-S evidence theory proposed in this paper can improve diagnosis precision and reduce the uncertainty of the diagnosis.

5. Conclusion

In order to improve the accuracy of fault diagnosis through using multi-fault characteristic information, a fault diagnosis method based on information fusion is studied in this paper. D-S theory is introduced to realize multi information fusion. The experiment result shows that when using multi sensor signal, the reliability of the fault diagnosis method is more accurate and reasonable certainty. As a result, the proposed method can improve the accuracy and reliability of fault diagnosis remarkably.

Acknowledgements

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